Detecting Distributed SQL Injection Attacks in a Eucalyptus Cloud Environment

Alan Kebert, Bikramjit Banerjee, Juan Solano
School of Computing
The University of Southern Mississippi
Hattiesburg, MS 39402, USA
Alan.Kebert@eagles.usm.edu

Wanda Solano
National Center for Critical Information
Processing and Storage
National Aeronautics and Space Administration
Stennis Space Center, MS 39529, USA
Wanda.m.solano@nasa.gov

***Abstract*—The cloud computing environment offers malicious users the ability to spawn multiple instances of cloud nodes that are similar to virtual machines, except that they can have separate external IP addresses. In this paper we demonstrate how this ability can be exploited by an attacker to distribute his/her attack, in particular SQL injection attacks, in such a way that an intrusion detection system (IDS) could fail to identify this attack. To demonstrate this, we set up a small private cloud, established a vulnerable website in one instance, and placed an IDS within the cloud to monitor the network traffic. We found that an attacker could quite easily defeat the IDS by periodically altering its IP address. To detect such an attacker, we propose to use *multi-agent plan recognition,* where the multiple source IPs are considered as different agents who are mounting a collaborative attack. We show that such a formulation of this problem yields a more sophisticated approach to detecting SQL injection attacks within a cloud computing environment.**

Keywords—cloud computing; Distributed Attack; Eucalyptus; SNORT; Havij; OSSIM; MAPR

I. INTRODUCTION

Cloud computing offers new opportunities for software distribution, resource allocation, convenience, and information security for users, but it also creates new opportunities for malicious users to penetrate security layers and damage, destroy or steal data of other users. One advantage that a cloud computing environment offers to malicious users is the ability to spawn multiple instances of cloud nodes that are similar to virtual machines, except that they can have separate external IP addresses. In this paper we demonstrate how this ability can be exploited by an attacker to distribute his/her attack, in particular SQL injection attacks, in such a way that an intrusion detection system (IDS) could fail to identify this attack. To demonstrate this, we set up a small private cloud using the Eucalyptus [10] cloud environment, established a vulnerable website in one instance, and placed an IDS (open source OSSIM [11]) within the cloud to monitor the network traffic. We found that an attacker, using a freely available SQL injection tool (Havij) could quite easily defeat OSSIM by periodically altering its IP address, i.e., by hopping from one instance to another in the cloud.

To detect such an attacker, we propose to use *multi-agent plan recognition* [1][2][4][5], where the multiple source IPs are considered as different agents who are mounting a collaborative attack. We show that such a formulation of this problem yields a more sophisticated approach to detecting SQL injection attacks within a cloud computing environment.

II. RELATED WORK

In the past, very little work has been done to study security issues and strategies in a cloud computing environment. “Digital Forensics for Eucalyptus” [9] considered security vulnerabilities in a Eucalyptus cloud, and our work can be considered as an extension or a continuation of that work, since we not only address exploitation of some vulnerabilities of Eucalyptus cloud, but also how to detect a resulting attack, where existing IDS fail.

SQL injection continues to be a threat and is discussed in depth in "A classification of SQL-injection attacks and countermeasures” [3]. Although multiple methods exist to prevent or detect SQL injection attempts, these methods tend to focus on single actions. It can be difficult to differentiate a single action of an attack from normal traffic, so Security information and event management programs (SIEMs) try to correlate multiple activities with the plan of an attacker [6]. SIEM directives typically look for a pattern of activity from a single user to increase the reliability of an alert, but do not consider whether the actions of multiple agents have collectively achieved a malicious goal.

Multi-agent plan recognition [1][2][4][5] (MAPR) has been formalized and studied recently in abstract and theoretical settings, and to the best of our knowledge it has not been applied to any realistic cyber-security problem. Hence in this respect our work constitutes the first practical application of MAPR.

III. DESCRIPTION OF SETTING

In this section we describe how the various components of our system are setup, and how they operate. In succession, we

will describe the Eucalyptus cloud setup that we used, the Havij SQL injection tool and the network traffic sniffer Snort, which is used as a sensor by the security event manager OSSIM to generate its alerts. Finally we describe how a simple strategy of switching source IP address can defeat OSSIM.

A. Eucalyptus Cloud

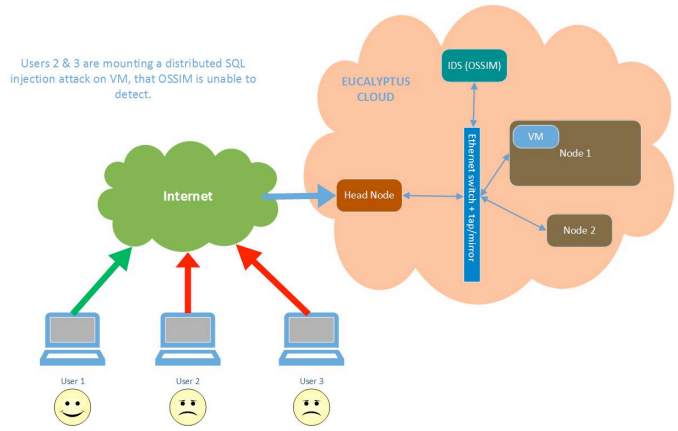


Fig. 1. The Eucalyptus Cloud Environment

The cloud environment on which this work is based is shown in Fig. 1. It contains three nodes, the head node – the manager of all communication with the external world – and two other nodes that offer various computational and storage resources to users. The communication between the head node and the other nodes are via an ethernet switch. An IDS (OSSIM) sniffs all packets passing through this switch. This gives OSSIM a vantage point to monitor any external attack on resources within the secondary nodes. In particular, we establish a vulnerable website within a VM in node 1. Fig. 1 also shows users outside the cloud accessing the cloud resources through the head node. Our attack computers were located outside the Eucalyptus cloud, but still able to compromise the database inside the cloud node.

B. Havij

In order to demonstrate an attack we used a program called Havij. Havij is a freely available SQL injection tool. SQL injection is the process of inserting arbitrary SQL code into a form whose input is queried against a SQL database. The form expects a user input, such as a username field on a login page, but if the text is not carefully sanitized a malicious user may place SQL commands into the field and cause the database to execute unintended commands. Havij facilitates this sort of activity by discovering the important field names needed for many SQL commands: database names, table names, and the columns of the tables. Havij can also reveal the contents of an unsecured database. It does this by first issuing a series of if-statements that test the length of field names, and then test the numerical value of the ascii characters representing individual characters of field names. Havij cannot ask the SQL database for the values directly, so it uses these comparisons to perform a binary search against a table of ascii numerical values. Each comparison will usually return zero immediately if false, but if true then an expensive MD5 benchmarking will be performed on a given string whose runtime will be reported to Havij. Based on this runtime, Havij can detect the binary outcome of the comparison. Fig. 2 shows a partial example of this process. The statements containing "if (Length" are part of a single binary search to determine the length (in this example 5) of the name of the database. The subsequent statements containing "if (ascii(substring" attempt to find the 5 characters one by one. The last statement of the form "if (ascii(substring((database()),x,1))=y,BENCHMARK…" that contains =y, marks the end of the process of finding the xth character. In this example, the 1st character has been determined to be "d", the ascii character with code 100. The search for the 2nd character starts next, but is not completed in Fig. 2.

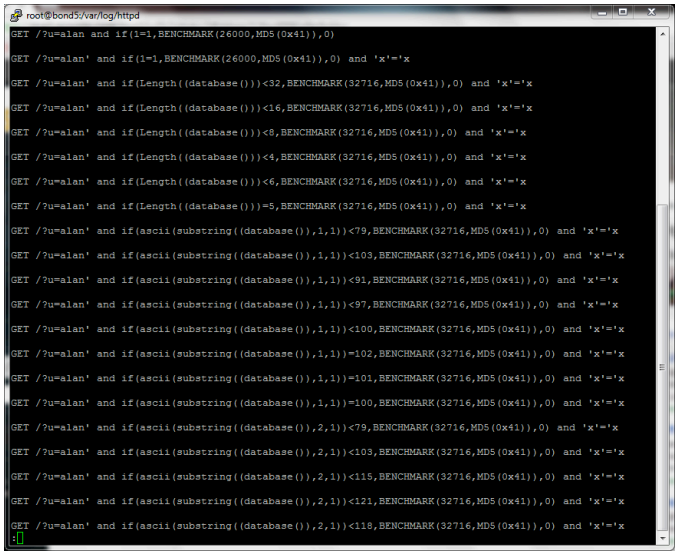


Fig. 2. Sample of (partial) tcpdump of a Havij attack formatted to be readable

Sometimes, perhaps due to delays in processing by the database, Havij receives non-zero runtimes for false statements that cause the binary search to go out of range or return a wrong length or character. This is usually inconsequential, as the search may be run again and comparing two searches allows the operator to fill in missing or wrong characters. In order to describe the database, Havij first runs these searches for length of the database name. Next it will perform binary search for that number of characters to determine the database name. Once it has the database name it can issue statements to determine the number of tables in the database. From there it will find each table name in a similar manner to the way it finds the database name, targeting the length of table names and then each character of the table names. It may then do this for column names in each table, and then for data contained in the table. Once the structure of the database is known, a hacker may execute arbitrary commands by filling in the appropriate values.

Fig. 3 shows an attack where Havij has determined the length of the database's name to be 5, and then conducted 5 separate binary searches for the characters in the database's name, discovering the name "dummy". Fig. 4 shows an advanced stage of this attack where Havij has discovered the

name of a table (“users”) in the database “dummy”, and used it to discover the three field names “user”, “email” and “password”. This attack can be manually continued through Havij, by selecting the columns in Fig. 4, and clicking “GetData”, to reveal the contents of the table, potentially compromising sensitive data.

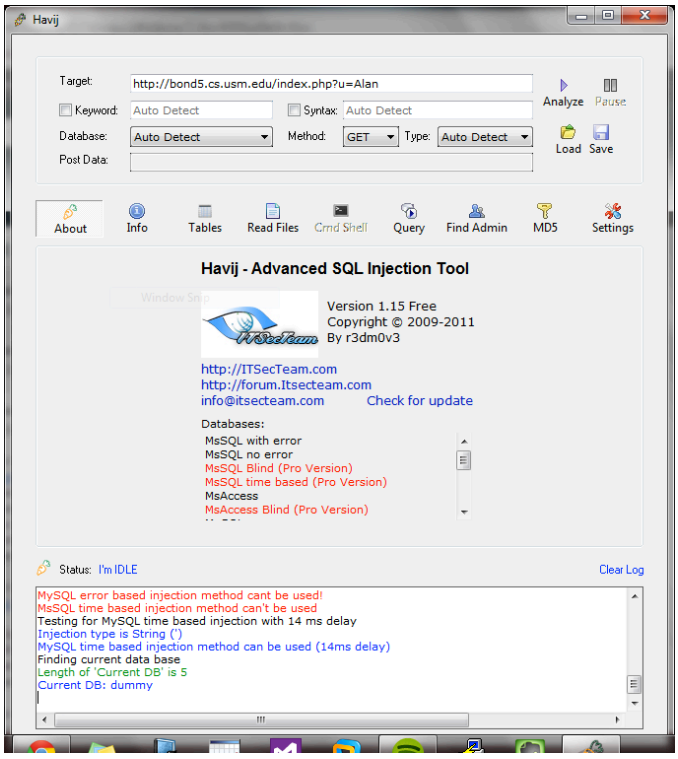


Fig. 3. Havij after finding the name of our database “dummy.”

C. *Snort*

We decided to use the popular packet sniffer Snort to detect these attacks. Snort compares the content of packets against a library of rules, and upon finding a packet whose contents match a rule, may raise an alert, log the packet, drop the packet, or perform some user defined function. With appropriate rules, Snort easily detects the Havij attack, but the functionality of Snort is greatly diminished by the large volume of alerts it raises. For example: our Snort rule library checks the packet content for the “BENCHMARK” command Havij uses to check the results of its binary search. This causes Snort to alert hundreds of times for one Havij attack. This problem is worse if valid traffic can contain suspicious content. For example, the character “ ‘ “ is often needed in SQL injection commands to end the query that is intended to run and allow the arbitrary commands to be inserted, but “ ‘ “ may also be part of valid names like “O’Reilly.” A snort rule that checks for “ ‘ “ in the packet will alert on the name “O’Reilly” unless additional conditions are added to the rule. Each additional condition to reduce false positives makes the rule easier to defeat. This results in a tradeoff between reducing false positives and decreasing detection rate. Since Snort only considers one packet at a time, it is very difficult to avoid false positives. This is where SIEMs come in.

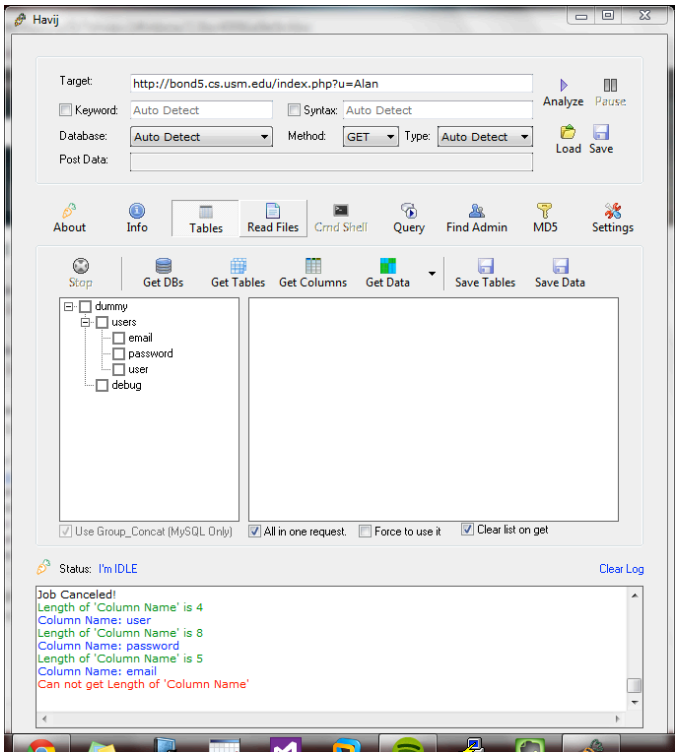
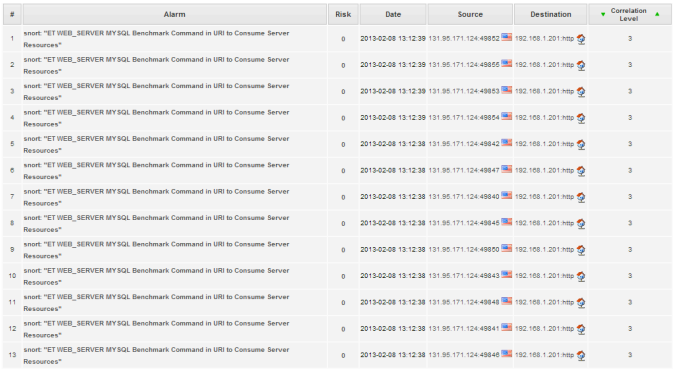


Fig. 4. Havij after identifying each column in the users table.

D. *SIEM/OSSIM*

SIEM stands for Security Information and Event Management. A SIEM uses tools like snort to detect various things, but interprets the results at a higher level before making alerts to the operator. We used the open source SIEM OSSIM for this project. OSSIM uses what its creators call a *correlation engine* to reduce false positives. The correlation engine relies on user created correlation directives to determine when to raise an alert. A correlation directive takes data from one or more sensors, like Snort, and tries to match them to patterns of malicious activity by organizing the data into correlation levels. The first level is always a single occurrence of a suspicious activity. Instead of alerting the operator immediately, the correlation directive moves to level two which will have a set of conditions and a timeout. If the conditions of level two are met before the timeout, the directive will elevate to level three and begin trying to meet a new set of conditions with a new timeout. The user defines how reliable each level is in indicating an attack, and this value along with the user assigned value of the assets that the SIEM is monitoring determines when an alert is actually raised. While the Havij attack generates hundreds of lower levels alerts, the correlation engine raises only one alarm. Fig. 5 shows the directive accumulating multiple snort activations while the far right column displays the correlation level of 3 where the single alert is raised.



#	Alarm	Risk	Date	Source	Destination	Correlation Level
1	snort: "ET WEB_SERVER MYSQL Benchmark Command in URI to Consume Server Resources"	0	2013-02-08 13:12:39	131.95.171.124:49852	192.168.1.201:http	3
2	snort: "ET WEB_SERVER MYSQL Benchmark Command in URI to Consume Server Resources"	0	2013-02-08 13:12:39	131.95.171.124:49855	192.168.1.201:http	3
3	snort: "ET WEB_SERVER MYSQL Benchmark Command in URI to Consume Server Resources"	0	2013-02-08 13:12:39	131.95.171.124:49853	192.168.1.201:http	3
4	snort: "ET WEB_SERVER MYSQL Benchmark Command in URI to Consume Server Resources"	0	2013-02-08 13:12:39	131.95.171.124:49854	192.168.1.201:http	3
5	snort: "ET WEB_SERVER MYSQL Benchmark Command in URI to Consume Server Resources"	0	2013-02-08 13:12:38	131.95.171.124:49842	192.168.1.201:http	3
6	snort: "ET WEB_SERVER MYSQL Benchmark Command in URI to Consume Server Resources"	0	2013-02-08 13:12:38	131.95.171.124:49847	192.168.1.201:http	3
7	snort: "ET WEB_SERVER MYSQL Benchmark Command in URI to Consume Server Resources"	0	2013-02-08 13:12:38	131.95.171.124:49840	192.168.1.201:http	3
8	snort: "ET WEB_SERVER MYSQL Benchmark Command in URI to Consume Server Resources"	0	2013-02-08 13:12:38	131.95.171.124:49845	192.168.1.201:http	3
9	snort: "ET WEB_SERVER MYSQL Benchmark Command in URI to Consume Server Resources"	0	2013-02-08 13:12:38	131.95.171.124:49850	192.168.1.201:http	3
10	snort: "ET WEB_SERVER MYSQL Benchmark Command in URI to Consume Server Resources"	0	2013-02-08 13:12:38	131.95.171.124:49843	192.168.1.201:http	3
11	snort: "ET WEB_SERVER MYSQL Benchmark Command in URI to Consume Server Resources"	0	2013-02-08 13:12:38	131.95.171.124:49849	192.168.1.201:http	3
12	snort: "ET WEB_SERVER MYSQL Benchmark Command in URI to Consume Server Resources"	0	2013-02-08 13:12:38	131.95.171.124:49841	192.168.1.201:http	3
13	snort: "ET WEB_SERVER MYSQL Benchmark Command in URI to Consume Server Resources"	0	2013-02-08 13:12:38	131.95.171.124:49846	192.168.1.201:http	3

Fig. 5. Snort activations and correlation level 3

This directive generates an alert at level three. It is activated by Snort detecting the BENCHMARK command in the packet content. Upon initial detection of the command and elevation to level two, it looks for fifty activations in 6 seconds between the same source and destination IPs that activated level one. If it sees fifty activations before the timeout, an alert will be raised and it will elevate to level 3 where it attempts to collect 1000 activations in the next 10 seconds between the same source and destination IPs. This directive easily picks up on a Havij attack, which generates hundreds of BENCHMARK commands within a few seconds in order to perform the binary searches. The details of the directive appear in Fig. 6.

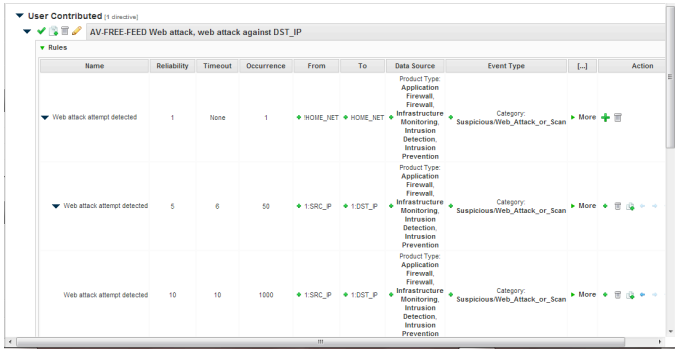


Fig. 6. The OSSIM correlation directive fired upon Havij attack.

E. *Simulating a Directive*

Unfortunately, we had difficulty getting our setup of OSSIM to perform consistently. Due to limited resources and time, we chose to simulate this directive with a python script and a tcpdump file. Tcpdump is a utility that captures traffic across a network in a widely used format. We used tcpdump to capture traffic from an attack. We then used a script to create a log of all the packets that contained the BENCHMARK command to simulate the snort activations. Using this data, our script counted up the number of activations before the timeout for each IP, elevating to level three in the same way that the OSSIM correlation would. An alert was then raised if enough activations were found. This is shown in the top part of Fig. 7.

Next, to simulate a distributed attack, we modified the IP addresses in the attack traffic so that after every 20 packets the IP would change, and these changes cycle within a set of 6 distinct IP addresses. This is a realistic simulation of a distributed attack, especially in a cloud computing environment, where a user can launch multiple instances with distinct IP addresses. By contrast, multiple VMs on a single machine do not acquire distinct external IP addresses (but they do acquire distinct internal addresses). After distributing the attack across the 6 distinct IP addresses, the script was still able to detect each attack, but since activations for any single IP address never exceeded the conditions, each distinct source IP remained at level two and raised no alarm. This is shown in the middle part of Fig. 7. However, the total number of packets sent by any single IP address is not under 50 (as shown in the bottom part of Fig. 7 for a single source), indicating that it is the temporal staggering of the packets that defeats level 2 of the directive, not a straightforward distribution of the packets among multiple sources which would make each source count fall under the threshold of 50 packets. In general, for any directive expecting x activations within time t before raising an alarm, n activations must be spread over more than (n/x) IP addresses such that an IP address is not reused before t, where lowering x makes it harder to slip past but more likely to raise false alarms.

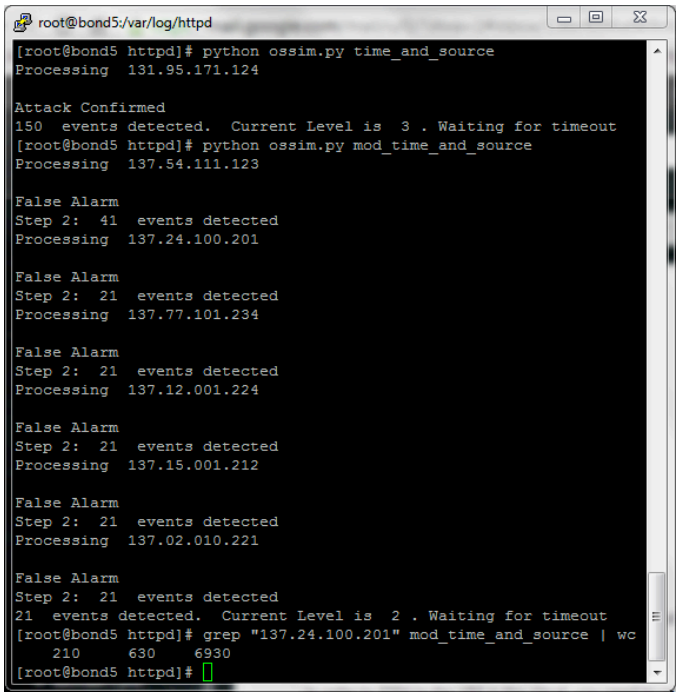


Fig. 7. Top: The attack from a single IP source, that raises an alert from the correlation angine. Middle: Attack spread across 6 source IP addresses. Events are detected but level 2 is not passed for any source, so no alert is raised by the correlation engine. Bottom: A single IP source sends more than 50 packets (210 packets) in all, showing that level 2 was defeated by temporal staggering of the packets.

IV. MULTI-AGENT PLAN RECOGNITION

Multi-agent plan recognition (MAPR) refers to the problem of explaining the observed behavior trace of multiple agents by identifying the (dynamic) team-structures and the team

plans (based on a given plan library) being executed, as well as predicting their future behavior [1][2].

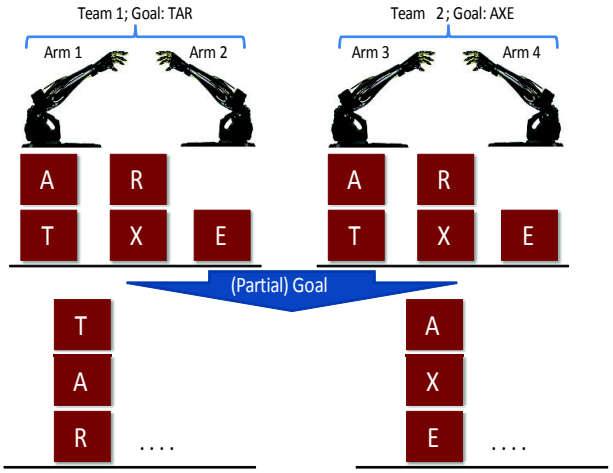


Fig. 8. Multi-agent blocks world example.

Arm 1	Arm 2	Arm 3	Arm 4
(unstack R X)	(unstack A T)	(unstack R X)	(unstack A T)
(put-down R)	(put-down A)	(put-down R)	(put-down A)
(noop)	(noop)	(noop)	(pick-up X)
(pick-up A)	(pick-up T)	(pick-up A)	(stack X E)
(stack A R)	(noop)	(stack A X)	(noop)
(noop)	(stack T A)	(noop)	(noop)

Assembles TAR

Assembles AXE

Assembles TAX

Fig. 9. Trace of activities of 4 robotic arms, shown in Fig. 8

We first illustrate MAPR in a multi-agent blocks word domain, shown in Fig. 8, Fig. 9, and Fig. 10, using standard PDDL operators. In Fig. 8 we see two teams of robotic arms assemble (i.e., spell out) the goal words ``TAR" and ``AXE" from separate stacks, starting from the (not necessarily) same initial configuration. Fig. 9 shows the trace of 6 steps of activities of the 4 robotic arms available to the (remote) recognizer, who is not aware of the team-structure (i.e., the mapping of agent-id to stack-id). This assumption partly models the realistic incomplete information under which the recognizer must operate. While arms 1 and 2 appear to jointly assemble ``TAR", and arms 3 and 4 appear to jointly assemble ``AXE", arms 2 and 3 seem to assemble ``TAX" as well, creating ambiguity for the recognizer. The key insight is to *partition* the trace into non-overlapping team plans, such that invalid teams (such as the supposed team of agents 2 and 3) fail to yield a complete partition hypothesis. In this example, agents 1 and 4 would be executing illegal plans individually, or building separate stacks as a team, neither of which yields a valid partition hypothesis. Fig. 10 shows a (non-unique) plan from the library, for start state in Fig. 8 and goal ``TAR", in the form of a plan graph. This is a graph based on the partially ordered set of steps needed to achieve a goal from a start state, with added constraints for multi-agency: *role constraints* (which steps need to be performed by the same agent) and *concurrency constraints* (which steps need to be executed simultaneously; not needed in this illustration). The above illustration is adopted from a previous paper by the authors [2].

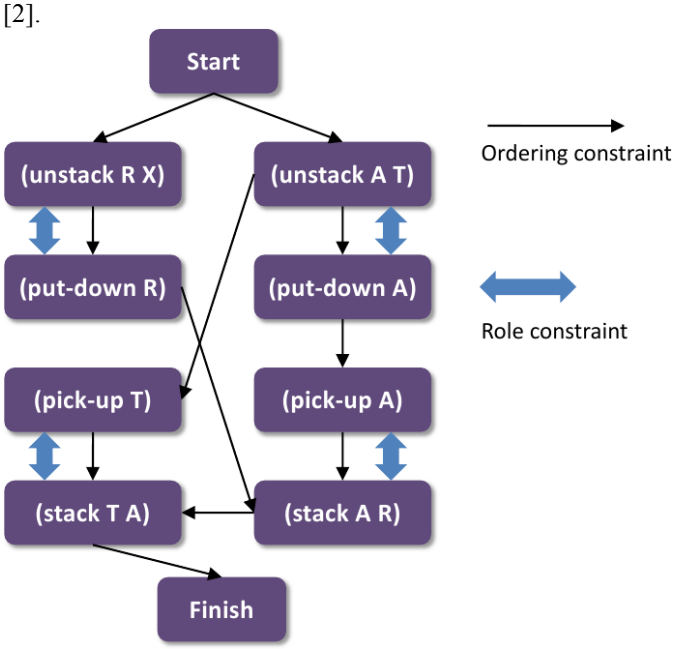


Fig. 10. A plan graph for the blocks world example.

V. Application of MAPR for Detection of Havij Attack

The SQL injection attack of Havij follows a pattern that can yield the abstract plan graph shown in Fig. 11.

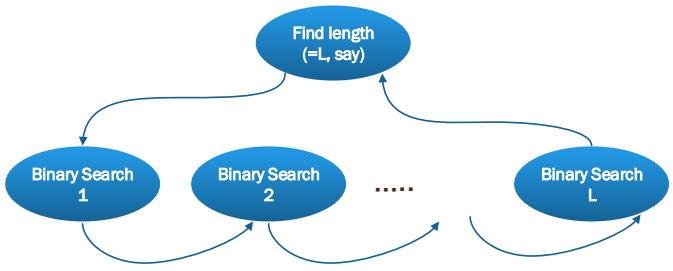


Fig. 11. Abstract plan graph corresponding to Havij attack

Here a binary search first finds the length of a certain field, say L. Then L binary searches are done in succession, followed by a return to the top (abstract) action. Suppose the *i*th binary search returns a character that is used to fill the *i*th

character of a string *s*. Then the string *s*[1:L] will be a part of the query used in the next search, e.g., after the name of a database is found this way, the queries to detect the names of tables in that database will include the name of the database already found. A string that differs by only a few characters from the database name used later should still be accepted because of the occasional false positives in the benchmark command. This pattern repeats to find the names of tables in the database using the database name, and then again to find the column names in a table using that table's name.

A solution to the problem of limiting false positives while still detecting an attack that is spread across multiple agents is to use plan recognition. Rather than relying on a single IP generating sufficient suspicious activity to raise an alert, a plan recognition algorithm searches input from all users to see if steps in a plan have been completed. For this pattern an algorithm would find the length command and then identify the search result by finding the last "=" or equivalent symbol. It would then look for that number of binary searches using the ascii and substring commands. If it sees these actions it is reasonable to assume that a field name has been found whether spread across multiple agents or not.

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